

Example of Frisch-Waugh Theorem

The Frisch-Waugh theorem says that the multiple regression coefficient of any single variable can also be obtained by first netting out the effect of other variable(s) in the regression model from both the dependent variable and the independent variable.

$$\hat{\beta}_1 = (X_1' M_2' M_2 X_1)^{-1} X_1' M_2' M_2 y = (X_1' X_1)^{-1} X_1' y - (X_1' X_1)^{-1} X_1' X_2 \beta_2$$

In practice this means regressing the residuals when y is regressed on X₂, (M₂y), on the residuals from when X₁ is regressed on X₂, (M₂X₁)

First regress the dependent variable on the X₂ variable (in this case London)

```
. reg grosspay london
```

Source	SS	df	MS	Number of obs =	12266
Model	2998066.02	1	2998066.02	F(1, 12264) =	18.73
Residual	1.9629e+09	12264	160055.968	Prob > F =	0.0000
Total	1.9659e+09	12265	160287.359	R-squared =	0.0015
				Adj R-squared =	0.0014
				Root MSE =	400.07

grosspay	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
london	50.70394	11.7154	4.33	0.000	27.73992 73.66797
_cons	232.5472	3.821297	60.86	0.000	225.0568 240.0375

```
. predict uhat1, resid
```

and save the residuals (named uhat1). This gives M₂y

Next regress the X₁ variable on the X₂ variable and save these residuals (named uhat2). This gives M₂X₁

```
. reg age london
```

Source	SS	df	MS	Number of obs =	12266
Model	2681.55785	1	2681.55785	F(1, 12264) =	21.36
Residual	1539528.39	12264	125.532322	Prob > F =	0.0000
Total	1542209.95	12265	125.740722	R-squared =	0.0017
				Adj R-squared =	0.0017
				Root MSE =	11.204

age	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
london	-1.516403	.3280945	-4.62	0.000	-2.15952 -.8732865
_cons	40.01296	.107017	373.89	0.000	39.80318 40.22273

```
. predict uhat2, resid
```

Now regress the residuals \hat{y}_2 on the residuals M_2X_1

```
. reg uhat1 uhat2
```

Source	SS	df	MS			
Model	473241.472	1	473241.472	Number of obs =	12266	
Residual	1.9625e+09	12264	160017.382	F(1, 12264) =	2.96	
Total	1.9629e+09	12265	160042.92	Prob > F =	0.0855	
				R-squared =	0.0002	
				Adj R-squared =	0.0002	
				Root MSE =	400.02	

uhat1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
uhat2	.5544311	.3223961	1.72	0.086	-.077516	1.186378
_cons	2.02e-07	3.61187	0.00	1.000	-7.079833	7.079834

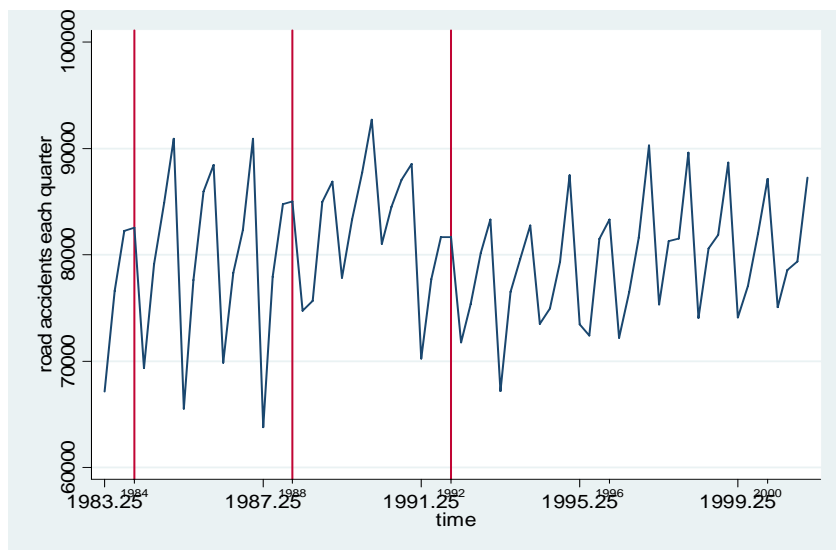
and check that this is the same as in the multiple regression (it is)

```
. reg grosspay age london
```

Source	SS	df	MS			
Model	3471307.55	2	1735653.78	Number of obs =	12266	
Residual	1.9625e+09	12263	160030.429	F(2, 12263) =	10.85	
Total	1.9659e+09	12265	160287.359	Prob > F =	0.0000	
				R-squared =	0.0018	
				Adj R-squared =	0.0016	
				Root MSE =	400.04	

grosspay	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
age	.5544311	.3224092	1.72	0.086	-.0775417	1.186404
london	51.54468	11.72466	4.40	0.000	28.5625	74.52687
_cons	210.3628	13.45452	15.64	0.000	183.9898	236.7357

In practice you will hardly ever use the residual approach to obtain multiple regression coefficients (one exception to this is if the X_2 variables capture seasonal or time effects, in which case you can think of the 2-step process as an alternative method of “de-seasonalising” or “detrending” both dependent and control variables such as exhibit strong trends or seasonality as in the road accidents data below). The usefulness of this exercise is that it helps makes clearer the partialing out nature of multiple regression.



```
twoway (line acc time), xlabel(1983.25(4)2000) xlabel(1984(4)2000) xline(1984 1988 1992) ytitle(road accidents each quarter)
```

Another way to think about partialling out is to recognise that the multivariate OLS estimate of any single variable can always be written as

$$\hat{\beta}_k = \frac{Cov(M_2 X_k, Y)}{Var(M_2 X_k)} \quad (\text{see lecture notes and exercise 1})$$

Consider an OLS regression of food share expenditure on total expenditure and age

```
use "C:\gea\food.dta", clear
```

The multivariate regression model is given by

```
. reg foodsh expnethsum age
```

Source	SS	df	MS			
Model	4290.50386	2	2145.25193	Number of obs =	200	
Residual	14387.5993	197	73.0334989	F(2, 197) =	29.37	
				Prob > F =	0.0000	
				R-squared =	0.2297	
				Adj R-squared =	0.2219	
Total	18678.1031	199	93.8598148	Root MSE =	8.546	

foodsh	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
expnethsum	-.0128509	.0021607	-5.95	0.000	-.0171119	-.0085898
age	.1023938	.0418339	2.45	0.015	.019894	.1848935
_cons	18.78057	2.657014	7.07	0.000	13.54072	24.02041

We are interested in understanding the estimated OLS coefficient on age in a multiple regression

Partialling out the effect of total expenditure on the food share

```
. reg foodsh expnethsum
```

Source	SS	df	MS			
Model	3852.96953	1	3852.96953	Number of obs =	200	
Residual	14825.1336	198	74.8744122	F(1, 198) =	51.46	
				Prob > F =	0.0000	
				R-squared =	0.2063	
				Adj R-squared =	0.2023	
Total	18678.1031	199	93.8598148	Root MSE =	8.653	

foodsh	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
expnethsum	-.0147015	.0020494	-7.17	0.000	-.018743	-.01066
_cons	24.87616	.9376504	26.53	0.000	23.0271	26.72522

saving the residual

```
. predict yhat2 if e(sample), resid
```

Partialling out the effect of total expenditure on age

```
. reg age expnethsum
```

Source	SS	df	MS			
Model	5823.33649	1	5823.33649	Number of obs =	200	
Residual	41731.6185	198	210.76575	F(1, 198) =	27.63	
				Prob > F =	0.0000	
				R-squared =	0.1225	
				Adj R-squared =	0.1180	
Total	47554.955	199	238.969623	Root MSE =	14.518	

age	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
expnethsum	-.0180738	.0034385	-5.26	0.000	-.0248545	-.0112931
_cons	59.53094	1.573165	37.84	0.000	56.42863	62.63324

and saving this residual

```
. predict xhat2 if e(sample), resid
```

then regressing the first residual on the second (in a univariate model) we see the estimated OLS estimate on age from the multiple regression above

```
. reg yhat2 xhat2
```

Source	SS	df	MS			
Model	437.534334	1	437.534334	Number of obs =	200	
Residual	14387.5994	198	72.6646436	F(1, 198) =	6.02	
				Prob > F =	0.0150	
				R-squared =	0.0295	
				Adj R-squared =	0.0246	
				Root MSE =	8.5244	
Total	14825.1338	199	74.4981597			

yhat2	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
xhat2	.1023938	.0417281	2.45	0.015	.0201051	.1846824
_cons	6.26e-09	.602763	0.00	1.000	-1.188659	1.188659

```
. predict ahat if e(sample)  
(option xb assumed; fitted values)
```

```
. sort xhat2
```

Graphing this relationship

```
. two (scatter yhat2 xhat2) (line ahat xhat2)
```

